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Artificial Intelligence and Its Business Implications in the Automotive Industry

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Abstract

Research background: Artificial intelligence transforms industrial activities, particularly in the automotive sector, where companies face pressure to improve efficiency and competitiveness. Existing research highlights AI as a driver of operational and strategic advancement, yet empirical evidence on its financial impact remains limited. This study contributes to the literature by analysing how AI adoption influences financial outcomes of major automobile manufacturers.
Purpose of the article: The purpose of this article is to assess whether the implementation of artificial intelligence is associated with significant changes in selected financial indicators. The study applies a quantitative approach to evaluate the relationship between AI adoption and company performance, focusing on sales, year-over-year sales growth, return on equity, and profit after tax.
Methods: The empirical analysis is based on publicly available annual reports of three leading automobile manufacturers Mercedes-Benz, Audi, and Volkswagen, covering the period 2003–2023. The research design includes testing distributional characteristics of the financial data followed by the application of variance analysis methods suited to the results of the normality tests.
Findings & Value added: The results indicate that the impact of artificial intelligence on financial performance varies across companies and indicators. In several cases, statistically significant relationships were identified, suggesting that AI adoption may contribute to improved business outcomes. However, the effect is not uniform and depends on company-specific conditions and implementation strategies. The study adds value by demonstrating that while AI holds strong potential to enhance performance in the automotive industry, its benefits materialize only through context-sensitive integration. The findings provide relevant insights for both academics and practitioners and highlight opportunities for future research on AI's role in shaping industrial competitiveness.

Keywords: artificial intelligence; financial indicators; sales; automotive; industry

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1. Introduction

Artificial intelligence (AI) is increasingly influencing the current business environment. In the last decade, its importance has been further strengthened by the rapid development of digital technologies and automation. In practice, today it can be observed that AI is changing the nature of the functioning of many industries - from healthcare and finance to manufacturing, transportation, energy or e-commerce (Stamkou et al., 2025; Zhou et al., 2024). In terms of scope and speed of implementation, the automotive industry stands out in particular (Dorsch et al., 2025; Khushk et al., 2025), where AI is used not only in development and production, but also directly in the vehicles themselves. Today, car manufacturers are increasingly using intelligent systems to optimize processes, reduce costs or obtain relevant data to support decision-making. At the same time, however, a new dimension is emerging - cars themselves are turning into connected and "smart" products, which changes the way they interact with drivers and end customers (Gu et al., 2024).

In recent years, a number of studies have appeared in professional literature that analyze the benefits of artificial intelligence for businesses and society as a whole (Hessami et al., 2024; Surugiu et al., 2024; Era et al., 2024; Madan and Ashok, 2024; Sharma, 2024). Some studies emphasize the positive impact of AI on productivity and production efficiency, others point to the benefits in the area of security or personalization of services, nevertheless most of them emphasize also potential risks and concerns. Most risks are associated with dependence on automated systems, the possible loss of jobs, or issues related to data protection and ethical dilemmas (Broady et al., 2025). In the automotive sector, the discussion is focused on the impact of AI on financial metrics. There is no consensus on which approaches are best and what the true extent of AI’s impact on financial performance is.

Although the technological shift is obvious, the question of its real economic benefit is still not clearly answered. It is not always clear to what extent AI affects the financial indicators of companies and what differences exist between individual manufacturers in the effectiveness of its use. These questions are important not only for the companies themselves, but also for policymakers who are monitoring how AI is changing the competitiveness and innovation potential of the entire sector.

In order to better understand the impact of AI on the economic performance of automotive companies, this study focuses on the analysis of three leading companies in Central Europe – Volkswagen, Mercedes-Benz and Audi. The aim of this study is to determine whether the implementation of artificial intelligence has led to statistically significant changes in key financial indicators of these companies. Attention is paid to specific financial indicators, such as sales, year-on-year sales growth, return on equity and profit after tax. By comparing the period before and after the implementation of AI, it is possible to identify in which areas significant differences in performance were observed.

The results themselves show that AI can affect selected financial indicators, but the extent and nature of these impacts vary between individual companies. Differences in impacts may be related not only to the technologies used, but also to company strategies or the external environment. The findings of this analysis may be useful for managers, policymakers and the professional public who are looking for ways to optimize the use of artificial intelligence in the automotive sector and better understand its real economic benefits and risks.

This study is structured into several parts. The literature review provides an overview of the adoption of artificial intelligence and its development in various industries, as well as its role specifically in the automotive industry. This is followed by the methodology of the work, which includes the selection of companies, describes the data sources and selected analytical procedures. The results provide specific findings on the impact of AI on financial indicators, which are subsequently interpreted and compared in the broader context in the discussion section. The conclusion summarizes the main findings and offers recommendations for further research and practice.

1.1. Literature review

Jindal et al. (2024) explored the adoption of generative AI in healthcare systems, emphasizing the differences in value between traditional AI and GenAI. It suggests that while top-down deployment of traditional AI has shown clear benefits, GenAI may yield more value through bottom-up integration. The study highlights the importance of cultural adaptation within health systems to fully leverage GenAI's potential for patient outcomes. Roppelt et al. (2025) investigated the effective adoption of AI in healthcare through a multiple case study of 13 radiotherapy departments. It identifies key organisational, environmental, technological, and individual factors influencing AI adoption, with a strong emphasis on dedicated innovation strategies and holistic implementation. The study contributes to adoption theory and offers practical insights for healthcare managers aiming to leverage AI for efficiency and standardization.

Xu et al. (2024) analyzed over 6,500 bond credit ratings in China and finds that AI adoption by firms leads to improved credit ratings by enhancing productivity and information transparency. The effect is especially strong for non-state-owned, labor-intensive firms, and those with high earnings management. The article contributes to understanding the economic impacts of AI adoption and provides practical implications for lowering financing costs through digital innovation. Ramos et al. (2025) explored the adoption of Intelligent Virtual Assistants (IVAs) in the Portuguese banking sector, using the Technology Acceptance Model. Based on data from 154 users, it finds that perceived usefulness is the primary driver of adoption and usage, while factors like trust or anthropomorphism had no significant impact. The study underscores the importance of emphasizing functional utility in IVA design and provides insights for banks operating in mature digital markets.

Yang et al. (2024) examined AI adoption in professional service firms using the Technological-Organizational-Environmental (TOE) framework through a multiple case study of three auditing firms. The study identifies six key adoption factors, including technological affordances, innovation management, and regulatory context, which differ notably by firm size. Larger firms adopt AI more extensively but face regulatory challenges, while smaller firms struggle with readiness. The research offers a comprehensive view of AI adoption dynamics in the professional services sector. Frank et al. (2023) investigated how consumer trust influences the adoption of AI services with varying levels of autonomy across six service industries. Based on survey data from 503 consumers, they found that while trust in a company positively affects AI adoption, this effect diminishes when AI services have high autonomy. The findings highlight the importance of managing perceived autonomy in AI systems to maintain consumer trust and encourage adoption.

Vuong et al. (2021) highlighted the rapid development and expanding scope of artificial intelligence, particularly during the COVID-19 pandemic, where AI technologies such as machine learning, deep learning, and image processing were widely applied. Homemade AI-enabled software was the backbone of the study, providing a fast and automatic approach to collecting and analyzing social data. Moreover, the tool also allowed manually sorting the data, AI-generated word tokenizing in the Vietnamese language, and powerful visualization. Yan and Sun (2025) emphasized the development of artificial intelligence as a central force in the transition to smart manufacturing, with transformative effects on urban industry and energy use. Their study demonstrates how the increasing maturity and application of AI, particularly through smart industrial robots, has become instrumental in promoting technological innovation and restructuring industries. By empirically linking AI development to reduced carbon emission intensity in 275 Chinese cities, they underscore AI's evolution from emerging technology to a key driver of sustainable and intelligent urban growth.

Matamoros et al. (2025) underscored the transformative role of AI in the automotive industry, particularly in quality management and production optimization. Their work reviews key AI methods, such as deep learning and neural networks, used to enhance defect detection, automate inspections, and enable predictive maintenance. By improving precision and reducing reliance on manual processes, AI supports zero-defect manufacturing and real-time part tracking. The study highlights how AI integration is becoming essential for meeting the evolving standards of Industry 4.0 and 5.0 in automotive production. Soresini et al. (2025) highlighted the application of AI-driven machine learning techniques for fault detection in the automotive sector, specifically in testing Permanent Magnet Synchronous Motors (PMSM). Using advanced neural network architectures, such as Autoencoders (AEs), Convolutional Neural Networks (CNNs), and Long Short-Term Memory networks (LSTMs), the study identifies 1D CNN AEs as the most effective for accurate and efficient fault prediction. The AI-based approach enables semi-real-time monitoring of motor health under variable conditions, allowing early detection of issues like bearing faults and wear. This demonstrates AI's critical role in enhancing reliability and reducing downtime in automotive component testing. Stollenwerk et al. (2024) explored the potential of quantum-enhanced machine learning and optimization algorithms for future applications in the automotive industry. While current quantum computing capabilities remain limited, the study finds promising opportunities for long-term value, particularly in solving complex automotive problems. It emphasizes that early experimentation and cross-sector collaboration can prepare companies for future breakthroughs, positioning AI and quantum integration as a strategic focus for innovation in the automotive sector. Yan (2025) presented an AI-driven decision-making model for intelligent driving, combining finite state machines (FSM) with deep reinforcement learning (DRL) to optimize vehicle behavior in real-time. By factoring in the car's state, environmental context, and driver intent, the model enhances safety and responsiveness in complex driving scenarios. The integration of DRL enables adaptive learning from dynamic environments, showcasing AI's growing role in advancing intelligent and humanized automotive systems. Hossain et al. (2025) offered a taxonomic overview of vehicle health monitoring and fault diagnosis techniques across CVs, EVs, and AVs, highlighting the role of AI, IoT, and sensor fusion in improving maintenance accuracy, energy efficiency, and real-time decision-making. AI-driven methods showed up to 95% accuracy in fault detection and significant operational benefits. Similar to our research, the study emphasizes AI's measurable impact in the automotive sector.

2. Methodology

The main objective of the study was to examine the impact of AI implementation on key financial indicators in selected automotive companies. The scope was limited to three major European car manufacturers: Volkswagen, Audi and Mercedes-Benz. These companies were selected based on their active involvement in AI-driven innovation and the availability of comprehensive financial data over a longer period. This work relied exclusively on secondary data obtained from publicly available annual reports of the selected companies. These reports were obtained directly from the official websites of Volkswagen AG (2024), Audi AG (2024) and Mercedes-Benz Group AG (2024).

The analysis covered the fiscal years 2003 to 2023. In total, the analysis yielded 63 annual observations (21 years; 3 companies). The selected period allowed for examining developments in the years before the implementation of AI technologies on a larger scale, as well as the years during which AI deployment became more widespread in the automotive sector. The data extracted from the reports included the following financial indicators: (i) revenues (in billions of EUR); (ii) year over year (YoY) revenue growth (percentage change); (iii) return on equity (ROE, in %); and (iv) earnings after tax, referred to as earnings after tax (EAT, in billions of EUR).

To ensure consistency and comparability, all data were collected manually and double-checked for accuracy and subsequently imported into software. The selection of financial indicators was based on their relevance in assessing the financial performance and strategic direction of the companies. Revenue and revenue growth were selected as primary indicators of market success, while ROE and EAT served as metrics of internal profitability and shareholder value creation. These indicators were available for all three companies throughout the time period and provided a sufficient basis for quantitative analysis.

The basic methodology was based on statistical testing to determine whether the adoption of AI had a significant impact on the financial performance of the selected companies. The analysis used the following procedures.

1. Normality testing: The Shapiro-Wilk test was used to assess whether the financial variables followed a normal distribution. This step was crucial for selecting the appropriate parametric or non-parametric methods in the subsequent stages of the analysis.

2. Comparative analysis: Based on an internal review of the AI deployment timelines in each company, the data set was divided into two periods for each company: (i) pre-AI implementation (up to the year identified as the start of AI deployment); and (ii) post-AI implementation (from that year onwards). The classification was guided by a detailed review of company press releases, innovation reports and official strategic updates that indicated the start of systematic AI integration. For example, Mercedes-Benz was considered the company that had implemented AI more consistently since 2016, with similar cutoff points for the other two companies based on their specific developments.

3. Hypothesis testing: The study formulated hypotheses for each of the four financial indicators to assess whether the differences between the two periods were statistically significant. Depending on the distribution of the variables, either independent samples t-tests or nonparametric alternatives (such as the Mann-Whitney U test) were used. The significance level was set at $\alpha = 0.05$ for all tests.

4. Effect size assessment: Where appropriate, effect sizes (Cohen's *d* or *r*) were also reported to estimate the practical significance of the observed differences. All statistical analyses were performed using IBM SPSS Statistics version 28. Descriptive statistics and visualizations were first prepared in Microsoft Excel to gain an initial understanding of the data distribution. Graphical outputs included bar charts and trendlines for visualizing changes in key indicators over time.

Generative artificial intelligence (GenAI), specifically OpenAI's ChatGPT and QuillBot, were used solely for linguistic and stylistic enhancement of the English version of the manuscript. AI was not involved in data processing, analysis, or interpretation. All analytical procedures were independently conducted and verified by the authors using standard statistical techniques. As the study was based entirely on publicly available secondary data from corporate sources, it did not involve human or animal subjects, and no ethical approval was required.

3. Results

This section is divided into two main parts: verifying the assumptions of a normal distribution of selected economic indicators for each company, and then testing the statistical significance of the relationship between the use of AI and the selected indicators using ANOVA or Kruskal–Wallis test depending on the probability distribution function of the variable.

3.1. Verification of the normality of economic indicators

For each of the selected financial indicators (sales, year-on-year relative change in sales, ROE, EAT), a Shapiro–Wilk normality test was performed in IBM SPSS Statistics at a significance level of $\alpha=0.05$. The test was supplemented by Q-Q Plots and histograms. Based on the p-values and graphs a decision was made to use parametric or non-parametric tests further.

3.1.1. Audi AG

In all cases, the p-values exceeded 0.05, which means that evidence for rejecting the normal distribution of each indicator was not identified. Moreover, neither the histogram nor the Q-Q plots showed that the normality of the distribution was violated. Subsequently, a parametric ANOVA test was performed.

3.1.2. Volkswagen AG

Likewise, in the case of Volkswagen, the p-value was >0.05 for all four variables, and thus the assumption of normal distribution was not expected to be violated. This expectation was further verified by QQ plots and histogram. All indicators were also examined by a parametric ANOVA test.

3.1.3. Mercedes-Benz Group AG

In this case, it was found that three of the four indicators (sales, ROE, EAT) probably meet the normality criterion (no evidence for rejection was found), while the year-on-year relative change in sales showed a p-value <0.05 in the Shapiro-Wilk test. Results are in the table 1.

Table 1: Shapiro-Wilk statistic

Indicator	Shapiro-Wilk Statistic	df	Sig.
sales	0.946	20	0.316
year-on-year relative change in sales	0.824	20	0.002
ROE	0.931	20	0.164
EAT	0.915	20	0.079

Source: own elaboration

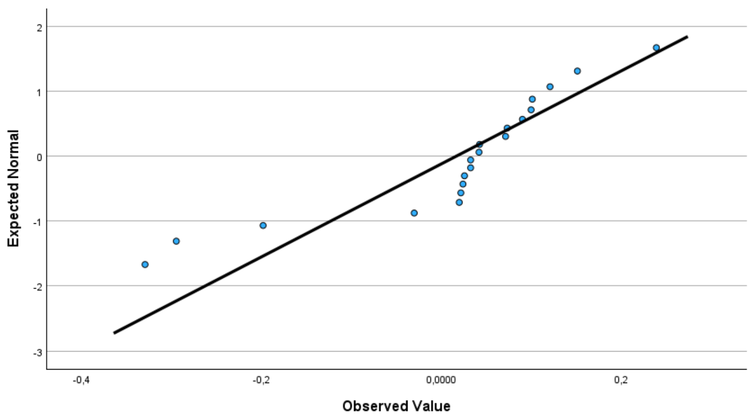
The table shows that the relative year-on-year change in sales could violate normality from a distribution perspective, so the decision was subsequently made after analyzing the Q-Q plots of normality and histogram. The following figures (Figure 1,2 and 3) show all of them.

Based on the Q-Q plots, histogram, and Shapiro-Willk test, it was determined that the data on the year-on-year relative change in sales do not meet the normality condition. Therefore, it was necessary to use the non-parametric Kruskal–Wallis test.

3.2. Statistical significance tests

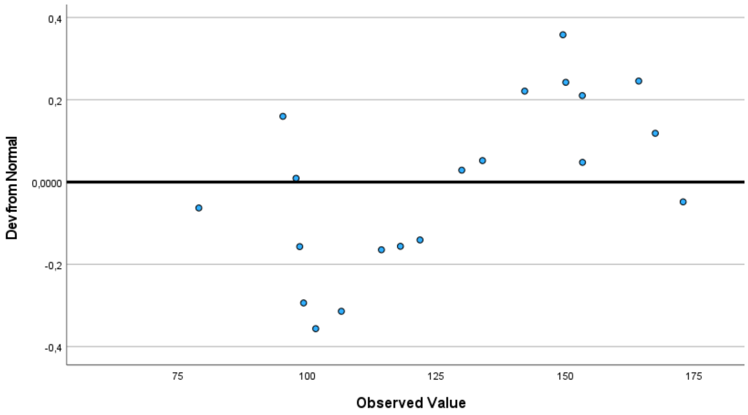
According to the results of the normality verification, the appropriate tests were selected for each company and indicator: (i) parametric ANOVA test (General Linear Model – Univariate) for pairs (AI vs. indicator), where normality was valid; and (ii) Kruskal–Wallis non-parametric test (Independent Samples) for the Mercedes-Benz indicator year-on-year relative change in sales.

Figure 1: Q-Q Plot of normality of the economic indicator year-on-year relative change in sales of Mercedes – Benz



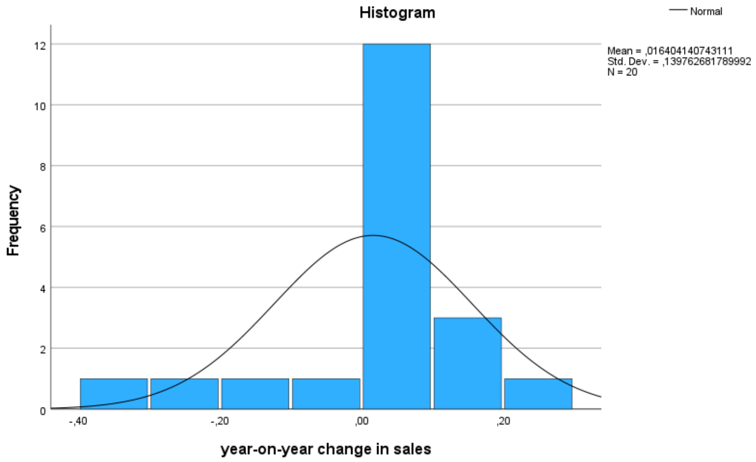
Source: own elaboration

Figure 2. Detrended Q-Q Plot of normality of the economic indicator year-on-year relative change in sales of Mercedes – Benz



Source: own elaboration

Figure 3. Histogram of the economic indicator year-on-year relative change in sales of Mercedes – Benz



Source: own elaboration

3.2.1. Audi AG

The results of the parametric ANOVA test of the selected Audi AG indicators are shown in the Table 2.

Table 2: General Linear Model – Univariate of Audi AG indicators

Dependent variable	**Sales in billion €**				
Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	1,963.901	1	1,963.90	21.87	<0.001
Intercept	4,6740.47	1	46,740.47	520.66	<0.001
AI	1,963.90	1	1,963.90	21.87	<0.001
Error	1,705.63	19	89.77		
Total	48,500.44	21			
Corrected Total	3,669.53	20			
R Squared 0.535 (Adjusted R Squared 0.511)					
Dependent variable	**Year-on-year relative change in sales**				
Corrected Model	0.0132	1	0.013	1.47	0.240
Intercept	0.052	1	0.052	5.95	0.025
AI	0.013	1	0.013	1.47	0.240
Error	0.156	18	0.009		
Total	0.234	20			
Corrected Total	0.169	19			
R Squared 0.076 (Adjusted R Squared 0.025)					

Table 2: Continued

Dependent variable	ROE				
Corrected Model	0.012	1	0.012	3.59	0.073
Intercept	0.645	1	0.645	189.40	<.001
AI	0.012	1	0.012	3.59	0.073
Error	0.065	19	0.003		
Total	0.807	21			
Corrected Total	0.077	20			
R Squared 0.159 (Adjusted R Squared 0.115)					
Dependent variable	**EAT in billion €**				
Corrected Model	18.384	1	18.38	6.93	0.016
Intercept	245.237	1	245.23	92.47	<.001
AI	18.381	1	18.38	6.93	0.016
Error	50.387	19	2.65		
Total	295.955	21			
Corrected Total	68.767	20			
R Squared 0.267 (Adjusted R Squared 0.229)					

Source: own elaboration

3.2.2. Volkswagen AG

The results of the parametric ANOVA test of the selected Vlokswagen AG indicators are shown in the following Table 3.

Table 3: General Linear Model – Univariate of Volkswagen AG indicators

Dependent variable	Sales in billion €				
Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	63,534.071	1	63,534.07	33.74	<.001
Intercept	751,283.92	1	751,283.92	399.06	<.001
AI	63,534.07	1	63,534.07	33.74	<.001
Error	35,769.90	19	1,882.62		
Total	789,266.54	21			
Corrected Total	99,303.97	20			
R Squared 0.640 (Adjusted R Squared 0.621)					
Dependent variable	**Year-on-year relative change in sales**				
Corrected Model	0.003	1	0.003	0.35	0.557
Intercept	0.091	1	0.091	10.66	0.004
AI	0.003	1	0.003	0.35	0.557
Error	0.153	18	0.008		
Total	0.257	20			
Corrected Total	0.156	19			
R Squared 0.019 (Adjusted R Squared -0.035)					
Dependent variable	**ROE**				
Corrected Model	0.003	1	0.003	0.66	0.426
Intercept	0.231	1	0.231	52.22	<.001
AI	0.003	1	0.003	0.66	0.426
Error	0.084	19	0.004		
Total	0.345	21			
Corrected Total	0.087	20			
R Squared 0.034 (Adjusted R Squared -0.017)					
Dependent variable	**EAT in billion €**				
Corrected Model	212.204	1	212.20	5.98	0.024
Intercept	1,729.36	1	1729.36	48.76	<.001
AI	212.20	1	212.20	5.98	0.024
Error	673.78	19	35.462		
Total	2,426.22	21			
Corrected Total	885.99	20			0.024
R Squared 0.240 (Adjusted R Squared 0.199)					

Source: own elaboration

3.2.1. Mercedes - Benz AG

The results of the parametric ANOVA test of the selected Mercedes - Benz AG indicators are shown in Table 4.

Table 4: General Linear Model – Univariate of Mercedes-Benz AG indicators

Dependent variable	**Sales in billion €**				
Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	4,072.111	1	4,072.11	7.10	0.015
Intercept	309,769.74	1	309,769.74	540.12	<.001
AI	4,072.11	1	4,072.11	7.10	0.015
Error	10,896.83	19	573.52		
Total	358,060.84	21			
Corrected Total	14,968.95	20			
R Squared 0.272 (Adjusted R Squared 0.234)					
Dependent variable	**ROE**				
Corrected Model	0.012	1	0.01	1.07	0.313
Intercept	0.26	1	0.26	38.11	<.001
AI	0.01	1	0.01	1.07	0.313
Error	0.13	19	0.01		
Total	0.42	21			
Corrected Total	0.14	20			
R Squared 0.054 (Adjusted R Squared 0.004)					
Dependent variable	**EAT in billion €**				
Corrected Model	168.133	1	168.13	6.35	0.021
Intercept	1,108.60	1	1,108.60	41.89	<.001
AI	168.13	1	168.13	6.35	0.021
Error	502.85	19	26.47		
Total	1,613.53	21			
Corrected Total	670.97	20			
R Squared 0.251 (Adjusted R Squared 0.211)					

Source: own elaboration

Since in the case of Mercedes - Benz AG, the indicator of year-on-year change in sales did not meet the conditions of normal distribution and normality was rejected, a non-parametric Kruskal–Wallis test was used to verify the impact of AI implementation on this indicator. The results are in Table 5.

Table 5: Kruskal–Wallis Test Summary for Year-on-Year Sales Change (Mercedes-Benz AG)

Independent-Samples Kruskal-Wallis Test Summary	
Total N	20
Test Statistic	0.245
Degree Of Freedom	1
Asymptotic Sig.(2-sided test)	0.621

Source: own elaboration

4. Discussion

The results obtained in this article represent an important contribution to the understanding of the impact of AI on the economic performance of companies in the automotive industry. The discussion focuses on the interpretation of statistical findings, their comparison with the current state of research and the suggestion of further directions in which research in this area could be pursued.

In the case of Audi AG, all four monitored economic indicators – sales, year-on-year change in sales, ROE and EAT – were verified in terms of normality of distribution and no deviations from normal distribution were detected. Based on this, a parametric ANOVA test was applied. The most significant impact of AI implementation was recorded for the sales indicator, where the value $F = 21.87$ and $p < 0.001$ indicate clear statistical significance. The significant impact of AI on EAT was also confirmed ($F = 6.93$; $p = 0.016$). In both cases, we can speak of a positive impact of AI on the economic performance of the company, which supports the hypothesis that the implementation of intelligent systems can increase production efficiency, prediction and decision-making processes. On the contrary, for the indicator year-on-year relative change in sales, the result was $p = 0.240$, which does not indicate statistical significance. This result can be interpreted as meaning that the impact of AI on the dynamics of sales growth may not be immediate; nevertheless, it might be reflected in the absolute value of sales rather than in their year-on-year change. For ROE (return on equity), the p value was just below the significance level ($p = 0.073$), which can be considered a borderline result. Although this is not a statistically significant difference at the 5% level, it indicates a possible trend that might require deeper investigation in the future with a larger sample set.

Also, in the case of Volkswagen, all variables were normally distributed, which allowed the use of ANOVA. Similar to Audi, AI proved to have a statistically significant impact on sales ($F = 33.74$; $p < 0.001$) as well as on EAT ($F = 5.98$; $p = 0.024$). These results confirm that the use of AI in the context of manufacturing, predictive maintenance and process optimization can have a positive impact on key financial indicators. On the other hand, the year-on-year change in sales ($p = 0.557$) and ROE ($p = 0.426$) did not show statistical significance. This result is consistent with the observation at Audi and may be related to the fact that these indicators are more sensitive to external factors (e.g. market conditions, development costs, geopolitical risks) that can mask the effects of AI.

In the case of Mercedes-Benz, the situation was more complex. Although the sales, ROE and EAT indicators were normally distributed and analyzed via ANOVA, the year-on-year relative change in sales was not normally distributed ($p = 0.002$), and therefore the non-parametric Kruskal–Wallis test was applied. The ANOVA results show that both sales and EAT showed a statistically significant effect of AI (sales: $F = 7.10$; $p = 0.015$; EAT: $F = 6.35$; $p = 0.021$), while ROE did not show this effect ($p = 0.313$). Here again, we observe a similar pattern as with Audi and Volkswagen: AI mainly affects absolute performance indicators (e.g. sales, profit), but less so relative or ratio indicators, which can also be affected by capital structure or dividend policy. The Kruskal–Wallis test for the year-on-year change in sales ($p = 0.621$) did not confirm statistical significance. This result is also important from a methodological point of view, as it confirms the need to verify the normality assumptions before applying the tests and adapt the methodology to the data analysis.

By comparing the results, it can be stated that all three analyzed companies recorded a positive statistically significant impact of AI on sales and EAT. This supports the hypothesis of a positive impact of AI on the performance of companies and at the same time points to the similarity between companies operating in the same industry and at a high technological level. At the same time, indicators such as ROE and year-on-year change in sales did not reach significance in most cases, which points to a more complex mechanism of their formation. The results confirm that AI can have a direct impact on increasing revenues and net profit of companies, but does not necessarily change profitability or year-on-year growth dynamics. This may also be related to the fact that the implementation of AI requires investments that are reflected in capital expenditures and can temporarily reduce ROE.

An interesting insight into the potential of artificial intelligence is also offered by a study by Kumar et al. (2024), which analyzes the relationship between AI capabilities (AIC), innovation strategies (exploratory – EXO, and exploitative – EXI) and research and development performance (RDP). The results of this study confirm the positive and statistically significant impact of AIC on innovation performance, with EXO and EXI playing a mediating effect between AI and R&D performance. Although this work did not focus directly on research and development performance, the findings on the positive impact of AI on indicators such as sales and profit are complementary to the above findings – they indicate that AI not only increases operational efficiency, but can also be a catalyst for innovations that translate into economic results in the long term. At the same time, the identified moderating effect of environmental dynamics (ED) is interesting, suggesting that the impact of AI can change depending on external conditions. This aspect may explain why some indicators (e.g. ROE or year-on-year growth) did not show statistical significance in our work – their sensitivity to changing market and technological conditions may be higher than for absolute performance indicators.

The results of the study by Kim et al. (2025) on the Korean Road Infrastructure Dataset (KRID) confirmed its high added value for research on AI in transportation – the dataset contains 34 infrastructure classes, covering a wide range of real-world conditions and has proven practical applicability in detecting damaged barriers or recognizing vehicles. Compared to our analysis in the automotive industry, there is a clear difference in orientation – the Korean study provides a data basis for technical applications of AI in infrastructure, while our results assess the significant impact of AI on the financial indicators of manufacturing companies (especially sales and EAT). However, both works point to the fundamental fact that the success of AI is manifested not only in the technological, but also in the economic dimension. The combination of robust infrastructure datasets and financial analyses from business practice offers a comprehensive view of how AI is transforming the entire automotive and transportation ecosystem.

The empirical study by Huang and Lin (2025) focused on the impact of AI implementation on business performance. Several indicators were analyzed. The researchers' results suggest that adopting AI technologies can positively affect the profitability and market value of companies, which is consistent with the results of our research, which showed a statistically significant relationship between AI implementation and sales and profit indicators. Interestingly, the impact on productivity in the aforementioned study was positive but statistically insignificant, which is consistent with our finding in the case of the ROE indicator, where the effect of AI was not significant. This study thus expands the context of our research by pointing out the diverse impact of AI across industries and companies, and at the same time supports the conclusion that the effective use of AI has the potential to significantly improve economic performance, although not equally in all areas.

A significant contribution to the discussion on the use of artificial intelligence in the automotive industry is the study by Hossain (2024). This work focuses on the design of a conceptual model for real-time monitoring of the technical condition of electric vehicles (EVs). The work shows that the implementation of AI into vehicle monitoring and diagnostic systems can significantly reduce operating costs, prevent unplanned downtime, and increase the overall safety and reliability of the vehicle. This trend is also confirmed by our finding that companies that introduce AI technologies into production and inspection processes experience higher efficiency and a reduction in the incidence of errors. Like our research, this study also points to the need to collect and process structured data, while subsequent analysis using machine and deep learning algorithms allows for the prediction of the remaining service life of individual components. From a practical point of view, this approach is especially crucial for electric vehicles, which contain several critical elements, such as batteries, electric motors, or transmission systems, the failure of which can lead to high costs or accidents.

Studies by Beinabadi et al. (2024), Rana and Khatri (2024), Forero et al. (2025), and Gupta et al. (2025) highlight the transformative impact of AI on various processes in the automotive industry – from predictive maintenance, to quality control, to strategic decision-making in R&D. While these studies focus mainly on the technical implementation of AI solutions and their benefits in the form of cost reduction or increased component reliability, our work focuses mainly on identifying statistically significant changes in financial indicators as a result of AI implementation.

These findings provide important recommendations for practice. First of all, they confirm that AI has the potential to significantly contribute to the growth of a company's absolute performance, especially sales and profit. At the same time, however, they indicate that the effect of AI may not be reflected in efficiency indicators (such as ROE) immediately. Companies should therefore not expect an immediate increase in profitability after implementing AI, but rather a long-term effect based on cost optimization, error reduction, predictive maintenance and streamlining of production lines. At the same time, companies should also sensitively consider the methodological aspects of evaluating the impacts of AI, because not all indicators reflect the impact of the technology in the same way.

For a deeper understanding of the effects of AI, it would be appropriate to expand the research to a larger sample of companies, or possibly to several sectors (e.g. finance, healthcare or logistics), where AI is also widely applied. At the same time, it would be appropriate to consider combining quantitative and qualitative methods, such as interviews with business representatives, which would help explain the context and strategies for introducing AI. Another promising direction would be to track the time lag of the impacts of AI – i.e. longitudinal studies that would capture longer-term effects on company performance.

5. Conclusions

The aim of this study was to analyze whether the implementation of AI in the automotive industry could significantly influence choosen financial indicators. Based on data from annual reports for the period 2003–2023, three automotive companies were analyzed: Mercedes-Benz, Audi, and Volkswagen. Four key indicators were assessed: sales, year-on-year change in sales, ROE, and EAT. The results showed that in all three companies, a statistically significant positive impact of AI on sales and EAT was recorded. This confirms the hypothesis that the implementation of AI can improve the performance of companies in terms of absolute financial indicators. However, in the case of relative indicators such as ROE and year-on-year change in sales, statistically significant differences were not confirmed. The study also showed that the impact of AI is not uniform across companies – differences in impacts may be related to technology adoption strategies, implementation time lags, or different levels of digitalization. A significant contribution of the work is therefore the comparative approach, which allows for a better understanding that the success of AI implementation depends on the context and conditions of a particular company.

In terms of practical recommendations, companies should not focus exclusively on short-term efficiency gains, but rather on the long-term strategic benefits that AI can bring - for example, in the area of predictive maintenance, error reduction or acceleration of decision-making processes. At the same time, it is necessary to sensitively evaluate which indicators truly reflect the impact of technologies and which may be distorted by other factors.

Three directions for further research appear promising: (i) expanding the sample of companies to include other industries where AI is actively applied; (ii) supplementing the quantitative analysis with qualitative methods, such as interviews with company representatives; and (iii) using longitudinal data to track the lagged impacts of AI on economic performance.

In conclusion, it can be stated that artificial intelligence in the automotive industry is already a significant factor shaping the economic performance of companies. However, in order to fully utilize its potential, it is necessary to approach its implementation systematically with an emphasis on strategy, adaptation of organizational culture, and sensitive assessment of economic effects.

Author contributions

All authors listed have made a substantial, direct and intellectual contribution to the work, and approved it for publication.

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Data Availability Statement

The data presented in this study are available in publicly accessible online repositories. All datasets analysed during the current research can be accessed at the following links:

- Volkswagen Group Annual Report 2024: https://annualreport2024.volkswagen-group.com/
- Mercedes-Benz Group Annual Report 2024: https://group.mercedes-benz.com/investors/reports-news/annual-reports/2024/
- Audi Sustainability Report 2024: https://www.audi.com/en/sustainability/sustainability-concept/sustainability-reports/report-2024/

Conflicts of Interest

The authors declare no conflict of interest.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used QuillBot and OpenAI's ChatGPT for linguistic and stylistic enhancement of the English version of the manuscript. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

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